engineering proceedings

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Proceeding Paper

Predictive Maintenance and Predictive Repair of Road Vehicles—Opportunities, Limitations and Practical Applications †

Jozsef Nagy * and Istvan Lakatos

Department of Road and Rail Vehicles, Audi Hungaria Vehicle Engineering Faculty, Szechenyi Istvan University Győr, H-9026 Győr, Hungary; lakatos@sze.hu

* Correspondence: nagy.jozsef@sze.hu; Tel.: +36-307678016

† Presented at the Sustainable Mobility and Transportation Symposium 2024, Győr, Hungary, 14–16 October 2024.

Abstract: With drastic increases in the complexity of road vehicles, increasing environmental and cost pressures have led to the obsolescence of previous fixed-schedule maintenance systems. The aerospace industry, following the road vehicle industry, is also beginning to use the predictive maintenance method increasingly widely. A possible next step for critical breakdowns could be a predictive service. While preventive maintenance is able to be used more frequently, the possibility of preventive repair is also limited to the fault symptoms, and is unsuitable for preventing fast-running breakdowns. Due to the current state of technological development in this area, it will take a few more years for lower-priced cars to catch up to the sensor and data structures of current premium-series vehicles, such that the mass use of these methods in road vehicles can become widespread.

Keywords: online collected vehicle data; predictive maintenance; predictive repair; machine learning; deep learning; recall; product liability; product field observing

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Citation: Nagy, J.; Lakatos, I. Predictive Maintenance and Predictive Repair of Road Vehicles—Opportunities, Limitations and Practical Applications. *Eng. Proc.* **2024**, *79*, 27. https://doi.org/10.3390/engproc2024079027

Academic Editors: András Lajos Nagy, Boglárka Eisinger Balassa, László Lendvai and Szabolcs Kocsis-Szürke

Published: 5 November 2024

1. Introduction

The possible failure of the systems of modern, increasingly complex road vehicles has a high cost beyond customer dissatisfaction. In previous practices, repair occurred after a breakdown. This is termed reactive maintenance or repair. This was followed by preventive maintenance or repair to increase operational safety [1]. Here, based on experience values, parts or substances are automatically changed after a certain operating hour or mileage, e.g., oil, air filters, timing belts, or chains. This is a very expensive method, so it is spread mainly in the aviation industry [2]. In the automotive industry, it has only become widespread for a few parts, e.g., those mentioned above, which has a strong impact on the reliability, fuel consumption, or service life of the car. The new trend in the automotive industry is predicting the timeliness of maintenance tasks using various methods [2]. Based on a state-of-the-art approach, we try to predict wear with the help of modeling supported by new technologies like AI/ML/NNs or digital twins and only install the new part immediately before maintenance is needed, or in the case of preventive replacement [1,3,4]. More systems in vehicles are covered with predictive solutions. The latest approach is to call the car into service for predictive repair in the event of a critical breakdown, e.g., to bring the car into service, before customer complaints.

2. Method of Predictive Maintenance/Repair Process Supported by Machine Learning in the Automotive Industry

Today, the application of data science to solve technical problems has spread in many areas, including the automotive industry.

Machine learning (ML) and neural networks (NN) can prove useful for determining trends and anomalies within the field of artificial intelligence (AI) [5]. Figure 1 below shows the data science process [6]: the first step is always the establishment of business/process/system understanding, as a basis for data understanding. Then, the data must be prepared, by eliminating empty or incorrect values from data tables or time series for modeling. For this purpose, Python is perhaps the most widely used language. Its advantages include the fact that it does not necessarily need to be installed (see Google Colab Python 3.10), contains various pre-made libraries and applications, and allows for the possibility of directly importing online or web data. To improve the model, it needs to be evaluated and trained. The data can consist of measured values from control unit sensors, DFCCs (diagnostic failure counter codes), or DTCs (diagnostic trouble codes); considering that many early DFCCs can cause a DTC, it is a better prediction method. The data can be collected online or offline in control units or internal/external data loggers.

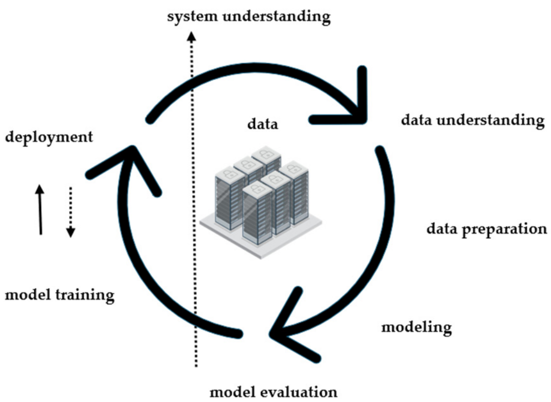

Figure 1. Process of data science/modeling: preparation of data (elimination of unnecessary/incorrect values, clustering . . .) and continuous training of model until target reliability is obtained.

2.1. Predictive Maintenance (PM) in the Automotive Sector

Until now, preventive maintenance has dominated the car repair industry. As a result of the much higher complexity of vehicles, possible field repair costs have increased drastically. To prevent this and reduce the TCO (total costs of ownership) at the same time, more manufacturers have started to use predictive maintenance in field service after it began to be implemented in manufacturing. Here, instead of the previous fixed-parts replacement intervals, flexible replacement times determined by artificial intelligence-based predictive models are used.

Typical systems eligible for predictive maintenance:

- high voltage (HV) battery systems [7,8];

  (delta gradient of isolation resistance, cell voltage balancing . . .)
- battery junction box (reed) relays (condition);
- brake pads (condition) [9];
- (wear of) tires [10];
- air conditioning (gas filling status);
- 12 V batteries (condition) (SoH: state of health);
- E-machine/HV batteries (coolant level) [11];
- (condition of) dampers (suspension) [12].

2.2. Preventive Repair or Service (PS) in the Automotive Sector

Preventive repair goes beyond predictive maintenance, where the customer typically receives information about upcoming maintenance activities through a mobile phone app. Here, we use AI- and ML-based predictive models to determine not only typically maintenance, but incidental as well, and specific fault-preventative fixes for critical, expensive, and tow-in related errors. Here, the customer receives a repair appointment from the service as part of a quasi-service field action.

However, a number of legal issues should be considered in this case:

- handling of cars within/outside of warranty period;
- warranty parts' cost charges to suppliers;
- reliability of models, since affected parts are still functional at the time of repair;
- product liability legislation: handling of tow-in vs. other issues with the same symptom, and business case approaches.

2.3. A Possible Process for Automotive Field Observation

1. definition of critical vehicle systems;
2. data collecting campaign—GDPR in the EU must be considered [13];
3. modeling (see Figure 1 above);
4. determining of affected cars;
5. service countermeasures with customer contact;

In addition to brand image and customer satisfaction being raised up, the system can prevent potential tow-ins. The warranty/repair costs can also be reduced by avoiding towing/rescuing (which means mobility-preventive measures).

The total repair costs of a car can be expressed as [4]:

$$\text{C sum} = \sum_{i=1}^{n} (\text{C reactive } + \text{C preventive } + \text{C predictive } - \text{C mobility}) \times \text{Ni} \quad (1)$$

where

Ni represents the number of inspections;
C reactive: costs of reactive repairs in the case of unpredictable failures;
C preventive: costs of preventive maintenance, e.g., oil and oil filters, air filters, V-belts, etc.;
C predictive: predictable repair costs, e.g., the replacing of high voltage battery modules;
C mob: the saving of mobility costs in the case of preventing tow-ins (rental cars, towing in. . .).

This C mob amount is a financial optimization potential for preventive repair vs. predictive maintenance [4]. The original formula has been added here with the mobility cost potential of preventive repair, see Figure 2.

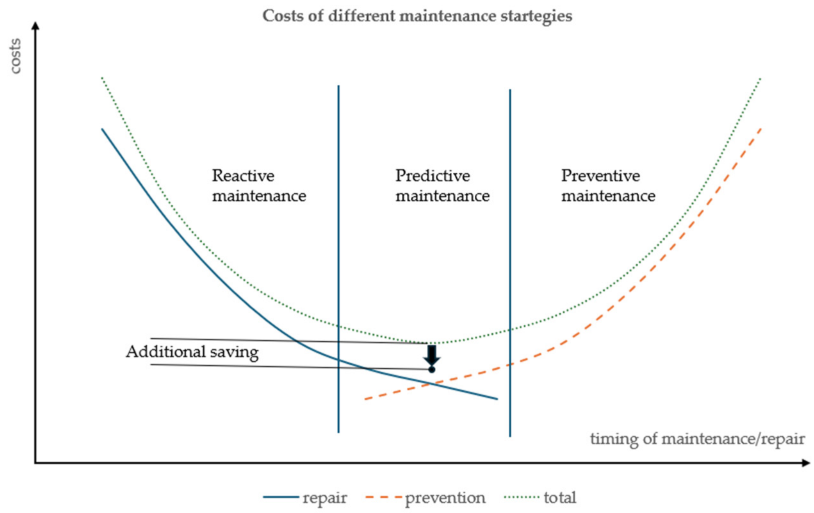

Figure 2. Costs of different maintenance strategies: reactive maintenance costs decrease, and preventive ones increase, depending on time. There is further cost potential (avoiding tow-in costs) by using predictive repair.

3. Results and Findings: Limits of Use Cases of Predictive Maintenance and Predictive Repair

There are limitations to using both methods. For example, the availability of different kinds of measured values (time series) over some time or at all. The measured data should be as current as possible, ideally real-time, otherwise either an outage prognosis will be made only after the complaint or, alternatively, before, but with too little time for preventive action.

The legal background must be considered too, especially regarding access to customer data and product liability [14]. In the case of a predictive repair of potentially critical claims, there are market surveillance regulations as a compliance factor [15].

In general, it is also not possible to collect any amount of data online for preventive purposes. One reason for this is the cost for mobile data that OEMs must pay, which increases the automaker's fixed costs.

At the same time, the data collection and transferring capacity of the car's data collection unit and the OEM backend infrastructure also set limits. Increasing these data storage and processing capabilities is also a cost factor (see also Section 2.3 point 2). Figure 3 below shows two typical use cases for the coolant-level monitoring method of the electric drive engine of a BEV (battery electric vehicle). The cheaper method builds a short circuit with the coolant water through its two poles. The disadvantage of this is that only two discrete signals are sent to the control unit: either the coolant liquid level is sufficient or too low. So, this method of diagnosis is not usable for both predictive methods.

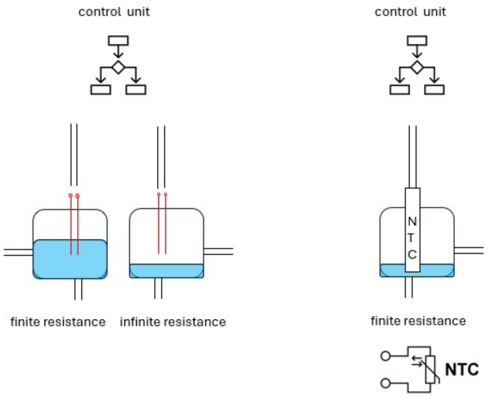

Figure 3. Methods of coolant-level monitoring in electric drive motors: there are no sensors with discrete signals, and parts with continuous signals are eligible for predictive purposes.

The NTC (negative temperature coefficient thermistor) resistor technique on the right side of the figure can be suitable as a basis for both predictive maintenance and preventive service at higher component costs, because it provides continuous feedback (signal) on the refrigerant level.

It follows from the above that due to possible additional sensors, data storage, and transmission costs, it is not advisable to use the predictive or preventive method in every use case. It can be applied even more narrowly due to the legal circumstances, e.g., regarding product liability [12]; therefore, it should be used to prevent critical errors such as tow-ins. Experience so far has shown that an important condition for applying both predictive methods is that the design must allow for the recording, storage, and transmission of certain measurement data from the vehicle. For this reason, it is advisable to start a "lessons learned" process as part of the review of the technical problem resolution process (manufacturing and field); see Figure 4 below [16].

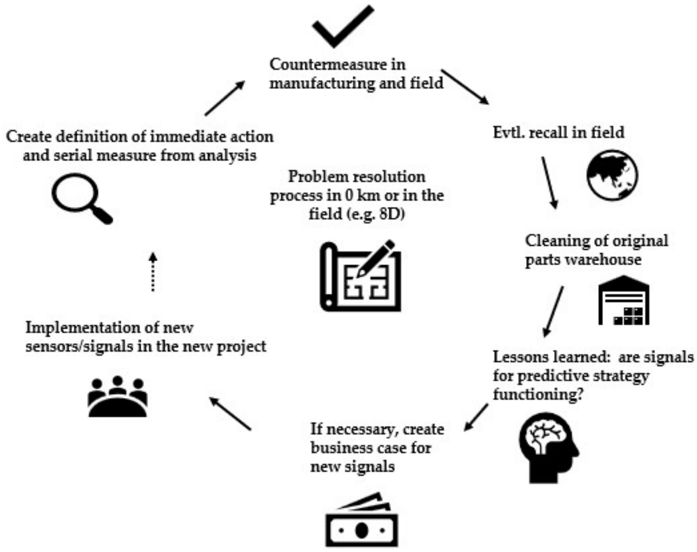

Figure 4. The RD (robust design) process: the requirements for new sensors include that there be an appropriate signal quantity/quality, as lessons learned has been defined as a key factor for the continuous improvement of predictable systems in future projects.

4. Conclusions: Starting of Lessons Learned Process Required

Predictive maintenance and repair will probably gain ground in the coming years.

The essence of predictive maintenance is in suggesting flexible intervals based on a model estimating component wear and tear instead of previously used fixed service intervals, thus optimizing operating costs. The aim of the new approach, preventive repair, is to predict potential critical breakdowns with the help of models and to order the vehicle to the workshop before they occur. So, the main difference between PM and PS is that PM provides information to the customer about the status of each system in the vehicle and the need for maintenance via the mobile app. At the same time, PS skips this and urgently orders it for service. At the same time, both methods require up-to-date, preferably online, data to intervene before the projected failure.

Here, it should be established whether data sampling of a given quality and frequency would be suitable as a basis for a predictive model. If not, it is advisable to review the future application for the necessary new sensor (business case).

The main message of this article is the focus on practical/processual implementation, with an informatic (data quantity and quality) and legal (data security, product liability, and market surveillance) background.

Since most key errors are currently software-related, it is necessary to conduct research where potential software errors can be predicted using mathematical models.

Author Contributions: Conceptualization: J.N.; supervision: I.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the European Union within the framework of the National Laboratory for Autonomous Systems (RRF-2.3.1-21-2022-00002).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data for this study is available upon request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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